Experimental Study 0f Drag Reduction Phenomena in the Horizontal Tube with Nano SiO_2 by Neural Network - Genetic Algorithm

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ABSTRACT: *In this study, nano-silica oxide's effect as a Drag Reducing Agent (DRA) of water flow in a 12.7 and 25.4 mm galvanized pipe was investigated. The studied parameters include Nano silica oxide concentration, Flow rate, temperature, and tube pipe diameter. To develop the conditions in preparing the Nano-particle on Drag Reduction (DR), nano-particles were provided in the top water-based fluid. To have a comprehensive analysis of process folding conditions, the experiments were carried out with three different drag-reducing concentration agents with three various temperatures and three different flow rates. Moreover, as a new method in this study, the experimental (Drag reduction percent) outputs were evaluated and analyzed using the Artificial neural network which is optimized by a genetic algorithm. In the consequence of algorithm genetic, the highest rate of drag reduction occurred at a horizontal pipeline 12.7 mm, temperature 41.07 °C, and a concentration of 0.628 with a 1441.84 flow rate was 25.84%.*

KEYWORDS: *Drag reduction; Pipeline; Nano SiO_2; Neural network; Single phase.*

INTRODUCTION

One of the problems in fluid transfer in pipes is pressure drop. In the past, the methods such as increasing the diameter of new pipeline units, creating loops, or increasing the number of pumps were used. Since they are so expensive and energy-consuming, they are the best alternative to injecting a drag-reducing agent into pipelines. In recent years, DRA (Drag Reducing Agent) has played an important role in reducing frictional pressure drop, and subsequently increasing liquid transmission pipelines' capacity.

The subject of drag reduction by adding a little amount of polymer was firstly reported by *Toms* (1977) [1]. While other kinds of additives are surfactants. *Gu et al.* (2010) [2], *Kamel* and *Subhash* (2010) [3], *Savins* (1967) [4], and

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Abubakar (2014) [5] studied soap solutions and observed that they also display drag reduction characteristics. Up to date, Polymeric Compounds with high molecular mass have been used to reduce drag [6-9]. An additional solid particle in micrometer size was considered for decades[10]. Much research was done on nano-particles effects on the heat transfer coefficient [11-16].

Some studied have been performed to reduce drag in pipes by nanofluids[17-23]. *Tao et al.* (1996) used a diamond nanoparticle additive in paraffin oil. The results show that posses a highly load-carrying capacity which decreases wear and friction [24].

Hu et al. (2002) used nanoparticle magnesium borate for lubricating oil additives. The results showed wear resistance and load-carrying capacity of 500 SN base oil were increased, and the oil's friction coefficient was decreased [25].

Thermal conductivity, viscosity, and stability of nanofluids containing Multi-Walled Carbon NanoTubes ($MWCNT_s$) stabilized by cationic chitosan were studied by *Phuoc et al.* (2011) Thermal conductivity increase from 2.3% to 13% with 0.5wt% to 3wt% $MWCNT_s$ (0.24 to 1.43 vol%). They observed that the increase in thermal conductivity was due to fluid viscosity.

MWCNT can be used to either increase or decline the viscosity due to the weight fractions for decline viscosity was reduction up to 20% [26].

Zulkifli et al. (2013) illustrated TiO_2 nanoparticles added to palm oil-based TMP (trimethyl propane) ester at 160 kg decreased the friction coefficient (15%) which decreased the wear scar diameter (11%) as compared to TMP ester without TiO_2 nano-sized [27].

In the field of SiO_2 nano-particles based on water, water - air, *Pouranfard et al.* (2014, 2015) have shown that the drag declines with decreasing pipe diameter and relative roughness and increasing concentration. Two mechanisms for drag reduction by nanofluids in streams within pipelines are possible. Firstly due to the changes in the rheology of the base fluid, the time which is needed to reach turbulence is delayed. The amount of drag in slow currents is negligible and so drag reduction along the entire pipeline route will happen. Also, reduction of tube roughness by the collision of nanoparticles in nanofluids and filling of micron cavities in the surface of the tube is a common subject. It should be mentioned this mechanism is specific to nanoparticles that have tribological properties and it is related due to their morphology and high strength [28, 29].

Gierczycki et al. (2015) studied drag reduction with CTAC/Nasal (cetyltrimethyl ammonium chloride/sodium salicylate) in the base fluids water and 1%vol Cuo based nanofluid. Results showed a maximum DR% decrease with larger diameter pipes, and Re number range is narrower at nanofluid than water solution [30].

Li et al. illustrated the nanoparticle SiC for increasing thermal conductivity in engine coolant. It is shown that the thermal conductivity increased by an increase in volume fraction and temperature. The highest thermal conductivity was 53.8% with o.5% vol nanoparticle and 50 ^{0}C temperature [31].

Chen et al.(2016) stated 0.01 wt% of nanodiamonds can have 32.5% reduction in the diameter of the wear scar and an increase of 119.3% in the contact pressure among the rubbing surfaces [32]. *Gulzar et al.*(2017) stated there is a stable dispersion of nano additives for nano lubricants. Nanoparticle Tio_2/Sio_2 (average particle size 50 nm) had appreciable dispersion capability which developed load-carry capacity, been anti-wear and friction reduce [33].

Zhang et al. (2018) were synthesized three cellulose esters, cellulose acetate butyrate, cellulose acetate-octanoate, and cellulose acetate-laurate, and inverted to nanoparticles and then added to paraffin oil. Tribological testing illustrated anti-wear and load-carrying properties increase with nano esters[34].

Ren et al. (2019) showed underwater drag reduction with a mico-nano composite structure. The simulation results illustrated an 89.49% drag reduction rate obtained. Water drag reduction benefits because of the decline in energy consumption [35].

In our study, SiO_2 nanoparticles as unexpansive and effective materials have been applied for the purpose of drag reduction. In this investigation, the effect of four influencing factors on drag reduction including flow rate, temperature, pipe diameter, and nanoparticles concentration have been studied. For the purpose of finding parameters' importance order and optimum values, the obtained experimental data have been used for modeling by the neural network system and optimized through the genetic algorithm. It should be mentioned until now, this type of computational programming has not been used for the purpose of drag reduction analysis.

The definition of reducing drag phenomenon

The method of adding additives, among them reducing factors, has a great importance. The essential additives for reducing drag can be polymer additives and nanocomposites which have sufficient degradation resistance and perform well. Injecting DRA (Drag Reducing Agent) into pipelines makes large vortices become smaller vortices in the turbulent flow, reducing the friction coefficient. The mechanism of drag reduction is still unclear and remains a significant challenge for researchers. *Virk et al.* (1975) can cite one of the best research on drag reduction. According to the results, the thickness of the wall layer increases with the presence of DRA. It increases the layer velocity profile and consequently reduces the contact surface and friction coefficient. The results of his work are presented in an equation due to the drag reduction process [36]. Besides, it can be said which all researchers observed the greatest drag reduction in Reynolds currents above 2500 [37].

The percentage of drag reduction is one of the drag reduction section criteria, which is defined as Equation (1) at a constant flow rate.

$$\mathrm{DR\%} = \left(1 - \frac{\Delta \mathrm{p\ nano}}{\Delta \mathrm{p\ solvent}}\right) \times 100 \tag{1}$$

Where Δp_{nano} and $\Delta p_{solvent}$ are pressure drops in the presence of additive and operating fluid, respectively.

EXPERIMENTAL SECTION

Experiment Structure

To analyze the drag reduction in a horizontal tube, we carried out in a build-up closed-loop liquid circulatory system. The schematic diagram for the experiment is shown in Fig. 1. It consists of two galvanized iron pipes with a diameter of 12.7 and 25.4 mm which is mounted on both sides of the tube, one meter apart with digital pressure and temperature sensors that is connected to a tank containing a thermal element and a thermal sensor PT100, centrifugal pump (model QB60), water flow meter.

The pressure in both ends of the tube was measured by a Swiss-made digital trafag 1.6 bar with 0.01mbar accuracy and read by a Digital Atones display made in Korea with an accuracy of 0.01. Then, the pressure drop was measured and the percentage of drag reduction calculated by Equation (1).

The fluid inside the tank is heated by a heating element and regulated by the PT100 sensor, and the temperature sensor reads the temperature at the two ends. The flow rate was measured by a bass instrument flowmeter (vertical rotameter) measuring from 250 to 2500 liters per hour with 5% precision. Nano SiO_2, %,20-30 nm by purchased Houston, TX77084, USA

Testing steps

First, ensure the inlet and outlet valves of the not tested pipeline are closed so that the inlet and outlet valves of the being tested pipeline will be open. The single-phase flow of water without the Nano SiO_2 enters the pipe under various operating conditions and temperatures. The studied parameters in the single-phase experiment include Nano SiO_2 concentration, temperature, flow rate, and tube diameter. Pour the desired concentration into the tank and heat, until it reaches the desired temperature. Adjust the flow rate by opening the valves, reading the flowmeter, and reading the pressure on both sides using a digital pressure gauge to calculate the pressure drop and the percentage of drag reduction.

To prepare the nano solution, remove the required amount of silica nanopowder as calculated by the following equation, stirred in the water solution with a 0.5% surfactant N,N,N,N Tetramethylethyldiamine and homogenized in the homogenizer at 400 watts and frequency of 20 kHz for half an hour and then poured the rest with water. Turn the volume up.

$$m_p=\varphi\times v_T\times\rho_p \tag{2}$$

$$vp=m_p\,/\rho_p \tag{3}$$

$$\varphi=v_p/v_T \tag{4}$$

φ=Nanoparticle volume fraction in nanofluid and v_T = total volume and ρ = Total density of nanoparticle

Data Analyzation

In this article, the combination of ANN and genetic algorithms is used. Temperature, concentration, flow rate, and diameter were also used to find the optimum values. First, the optimal structure for the above four values is obtained using ANN model, and the optimal amount of drag reduction is obtained using GA model and fitness function.

Optimization was performed by a genetic algorithm using GA in Toolbox Matlab. The optimization flowchart using ANN-GA hybrid model is given below.

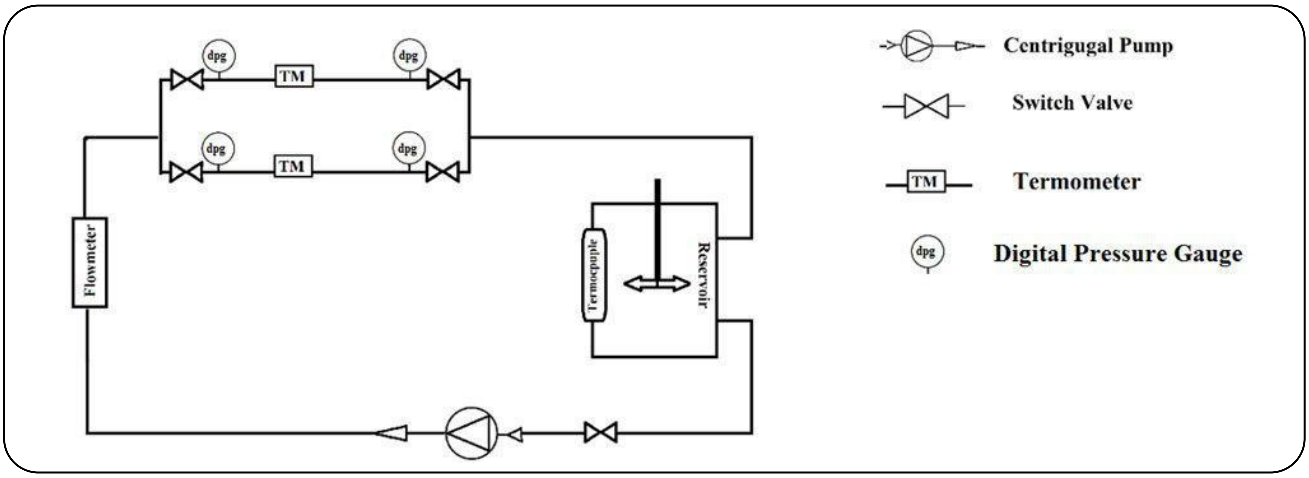

Fig. 1: Schematic diagram of closed-loop circulation system.

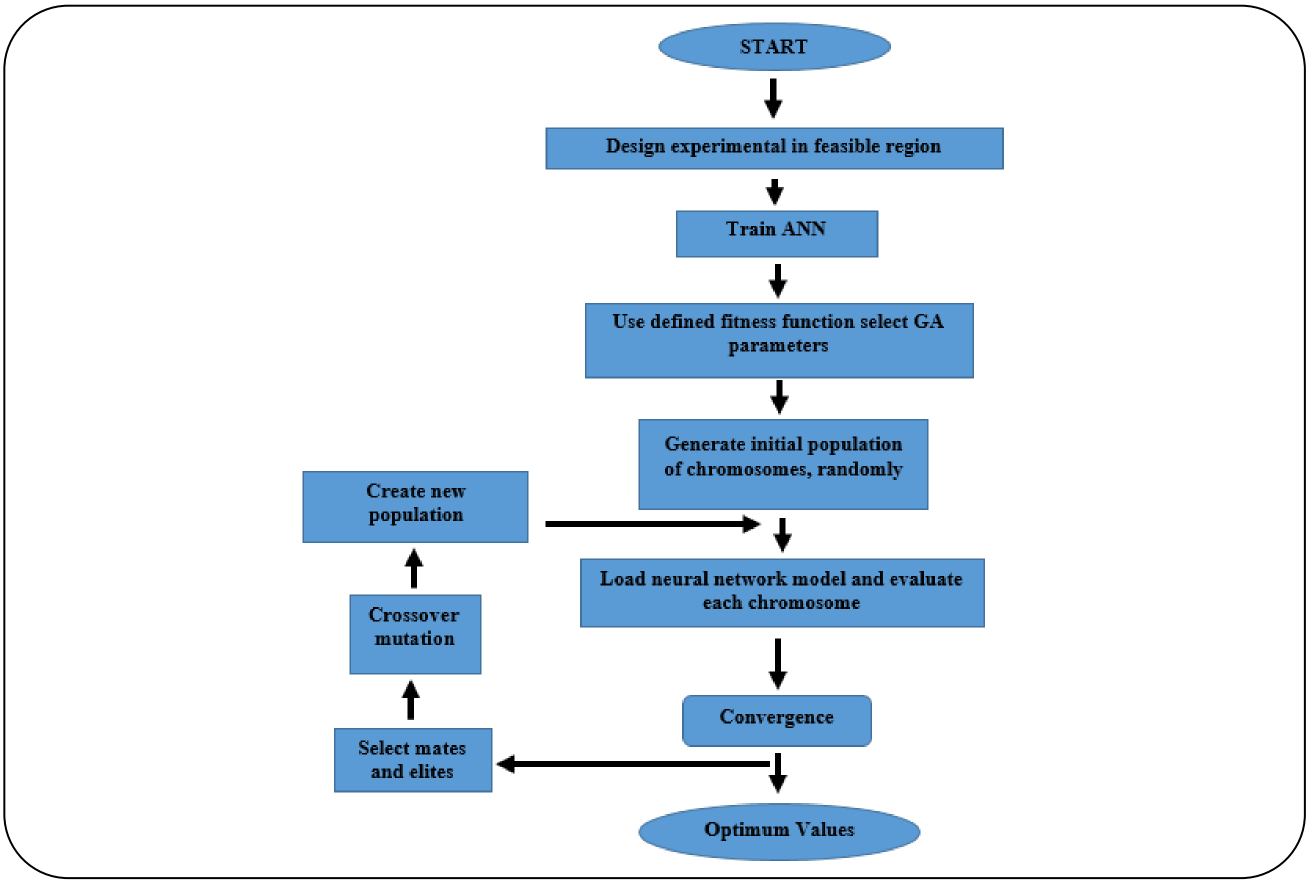

Fig. 2: Considered Model for combining genetic algorithm with the neural network.

Artificial Neural Network (ANN)

In this paper, the MultiLayer Perceptron (MLP) neural network was employed for effective variable modeling. This type can be mentioned as one of the most popular feedforward networks [38]. In this design, the network consists of several layers. The input layer comprises the neurons collecting the input value, the hidden layer(s) with interconnected neurons, and the output layer(s) with neurons reproducing output values. The number of neurons in the input and output layer respectively represents the number of independent and dependent variables [39]. The unique design of an ANN performed depends on the scientific problem.

The considered network in this investigation was simulated by computer code writing in MATLAB 8.1 software. The network was made up of an input layer with four neurons, consists of four variables related to drag reduction (Pipe Diameter, temperature, concentration, flow rate) and one output layer with one neuron, corresponding to the drag reduction. In this paper, it is assumed the application of one hidden layer in MLP structure is equally efficient as more hidden layers for problem-solving. Nevertheless, there is no overall principle to find several hidden layers. Due to this fact, a single hidden layer was applied for model designing in this paper [40,41]. The few neurons in the hidden layer negatively affect the relation modeling of input and output data while employing too many neurons leads to overfitting. Because of this reason, the quantity of neurons in the hidden layer as the most important parameter in the establishment of ANN model has to be optimized. The developed ANN consists of a vast number of neurons. Link strengths among neurons are diverse, and due to this fact, the signal passed through neurons has different weights [42].

In each neuron, to enhance or reduce the total of weighted inputs, bias requires to be computed. In the next stage, bypassing the weighted sum of inputs through the various transfer functions, as neuron activation functions, the output signal would be generated [43].

It should be mentioned, normalizing input data between -1 to +1 is essential before training (Eq. (5))

$$X_i = \left(2\frac{(x_i - x_{min})}{(x_{max} - x_{min})}\right) - 1 \tag{5}$$

In the equation, x_i and Xi are related to the natural and coded value regarding the ith variable, while x_{max} and x_{min} are the maximum and the minimum amount of each variable, respectively.

Evaluating the established model using k-fold cross validation investigations was done. For more evaluation, the designed ANN was studied due to the coefficient of determination, R^2, Average Relative Deviation % (ARD %), Mean Square Error (MSE), and Root Mean Square Error (RMSE). The statistical formula of these factors is given in equations (6-9) [42].

$$R^2 = 1 - \frac{\sum_{i=1}^{n}\left(y_{nn} - y_{exp}\right)^2}{\sum_{i=1}^{n}\left(y_{exp} - \overline{y}\right)^2} \tag{6}$$

$$ARD\% = \sum_{i=1}^{n}\left(\frac{\left|\left(y_{nn} - y_{exp}\right)\right|}{n.y_{exp}}\right) \times 100 \tag{7}$$

$$MSE = \left(\sum_{i=1}^{n}\left(y_{nn} - y_{exp}\right)^2 \Big/ n\right) \tag{8}$$

$$RMSE = \left(\sum_{i=1}^{n}\left(y_{nn} - y_{exp}\right)^2 \Big/ n\right)^{1/2} \tag{9}$$

In the above equations, n subscript represents the number of data, y_{exp} is the predicted value of the network in i'th observation, and y_{nn} is the actual output from the i'th test. The average of experimental output is represented by $\overline{y}$.

The validated networks were used for evaluating the effect of different input parameters on response. The relative significance of input variables was determined due to Eq. (10) [44].

$$I_j = \frac{\sum_{m=1}^{m=N_h}\left(\left(\frac{\left|W_{jm}^{ih}\right|}{\left(\sum_{k=1}^{N_i}\left|W_{jm}^{ih}\right|\right)}\right) \times \left|W_{mn}^{ho}\right|\right)}{\sum_{k=1}^{k=N_h}\left\{\sum_{m=1}^{m=N_h}\left(\left(\frac{\left|W_{jm}^{ih}\right|}{\left(\sum_{k=1}^{N_i}\left|W_{jm}^{ih}\right|\right)}\right) \times \left|W_{mn}^{ho}\right|\right)\right\}} \tag{10}$$

Where it means the relative significance of jth parameter. N_i and N_h are the numbers of neurons in the input and hidden layer, respectively. We indicate the link weights. 'K'; 'm' and 'n' indices present the input, hidden, and output neurons, sequentially.

RESULTS AND DISCUSSION

In this part of our study, pipe diameter, water temperature, Concentration of Nanofluid, and flow rate as necessary and useful process parameters on drag reduction were modeled by applying a multilayer feed-forward neural network. First, the training data (input data) related to the experimental Drag Reduction condition have been collected for neural network establishment. For ANN training, a group of input and output data is needed. So, the experimental data (144 points) were randomly separated into training and test sets (respectively 85%,15%). The training data were applied for network training, weight calculation, and network parameters computation. The test data were used for the validation and assessment of established model. The method which used for neuron number optimization in the generated ANN is presented in Fig. 3.

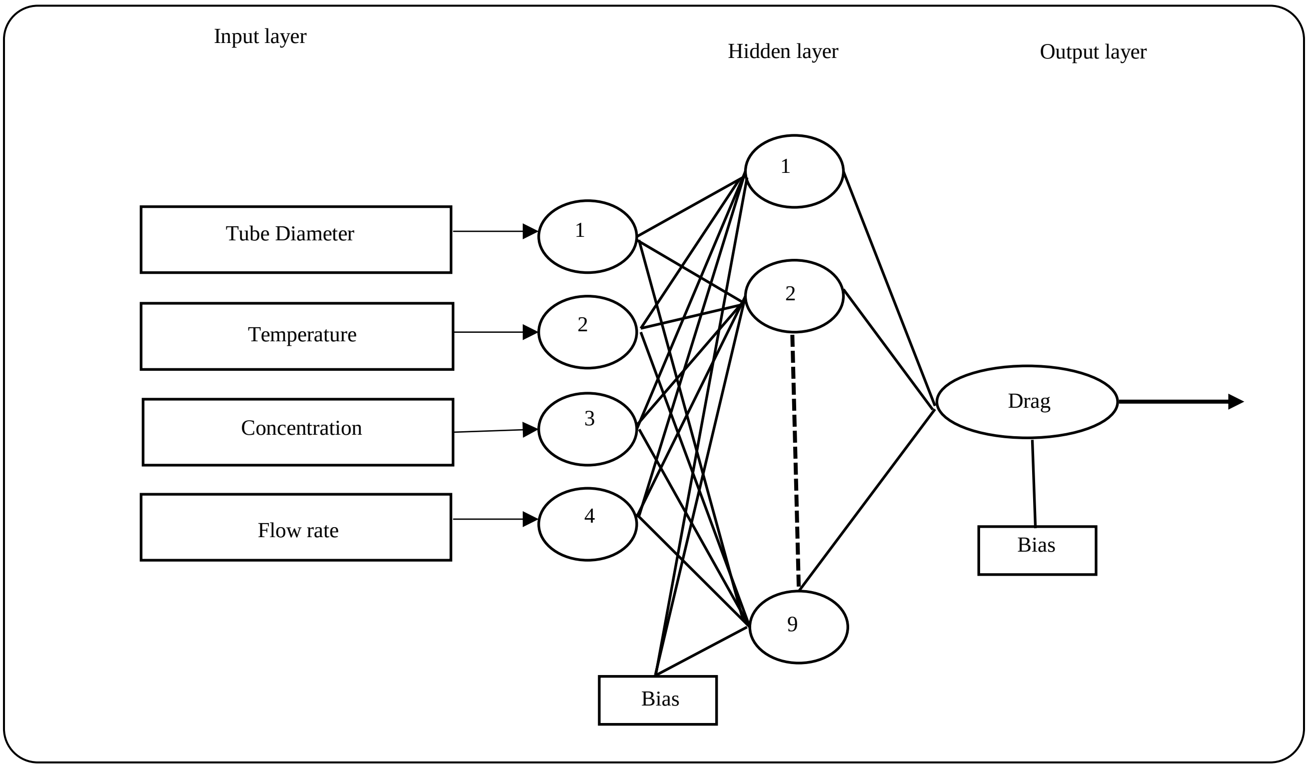

Fig. 3: Neural network topology, inputs, and outputs connected through a hidden layer.

In this manner, the number of hidden layer neurons was varied from 5-10. It is understood that the best performance of the network would be achieved with 9 neurons. The graphical schema of this network is presented in Fig. 4.

Investigating the obtained network generalization was processed by the method of k-fold cross-validation. In this manner,15% of the whole dataset was selected as test data, and the whole dataset was separated into 8 subsets, and for each subset, 7 data points randomly were chosen as test datasets. The remained data were applied for training and model validation. The relating test data for each sector is mentioned in Table 1.

The related RMSE values to training and testing data in the different subsets, along with the average values, are shown in Fig. 5. Nonsignificant change in the RMSE value causes appropriate generalization ability for different sectors of selected structures (4.9.1).

After the best topology establishment, calculating the network parameters as appropriate indices for evaluating the designed ANN was carried out. The amount of these parameters for the established network is shown in Table 2. The predicted drag reduction percent versus

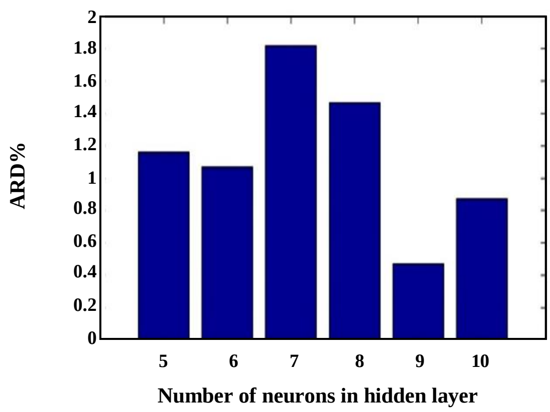

Fig. 4: ARD versus the number of neurons in the hidden layer.

the experimental values, which were collected for training and test data are shown in Fig 6.

As it is clear from this figure for training, and test sets of data, the whole data set R^2values is near to unity (more than 0.9982,0.9890,0.9998, respectively) which shows the predicted drag reduction percent is in good agreement with the empirical data. The resulted values for R^2 represent the established network is well trained

Table1. Test data in each category for the 8-fold cross-validation method.

Category	Test data						
1	7.9	13.2	7.9	15.9	11.6	13.5	19.2
2	19.5	7.9	12	11.9	13.5	13.5	20
3	19.5	8.7	19.5	15	11.6	13.5	6.0
4	13.2	13.5	19.2	13.5	19.2	6	12.3
5	19.5	8.7	12	15	19.2	13.5	12.3
6	19.5	11.9	19.2	19.2	9	15.5	7.5
7	7.9	19.5	15	13.5	13.5	9	15.5
8	7.9	19.5	11.9	19.2	9.5	13.5	19.2

Table 2: Performance of optimum ANN model (silica Nano oxide).

Source	Training	Test	All
R^2	0.9998	0.9890	0.9982
RMSE	0.0525	0.3747	0.1718
ARD	0.1169	1.9423	0.4719

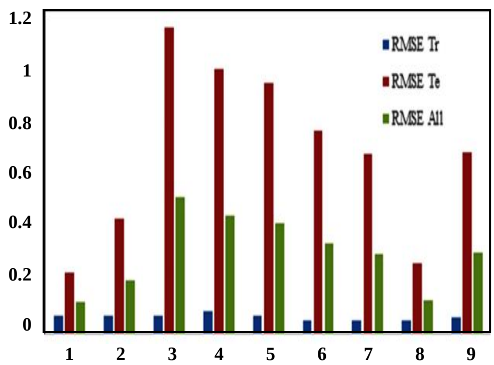

Fig. 5: RMSE values of each selected fold in 8-fold cross-validation method for optimal topology (4.9.1.

Fig. 7 shows the error histogram. This schema shows the error dispersal from the predicted amount.

$$Error=y_{nn}-y_{exp} \quad (11)$$

The disturbance near-zero illustrates the reliability of the established model.

Fig. 8**.** represents the relative significance of each variable. Considering this figure, the noticeable effect of all input variables on drag reduction percent is apparent.

The significance order of variable is as follow: concentration> Temprature> flow rate>tube diameter

Algorithm genetic model

This study's primary purpose is to determine the optimal parameters to obtain the most drag reduction using a genetic algorithm. Therefore, the optimization results were obtained from the genetic algorithm method using the coding model in Matlab. The starting and ending values for useful parameters are given in Table 3.

The optimum values for pipe diameter, temperature, concentration, and flow rate were obtained after applying the above conditions and executing the optimization program, as shown in Table 4. Under these conditions, the experimental drag reduction amount was 25.7%, which is in accordance with the predictive amount of 25.84%.

The chart of fitness values is shown below in Fig. 9. Optimization results have been achieved in 51 generations.

CONCLUSIONS

In the present study, a single-phase fluid flow laboratory model was designed. We chose nano SiO_2 to increase the percentage of drag reduction. Four parameters

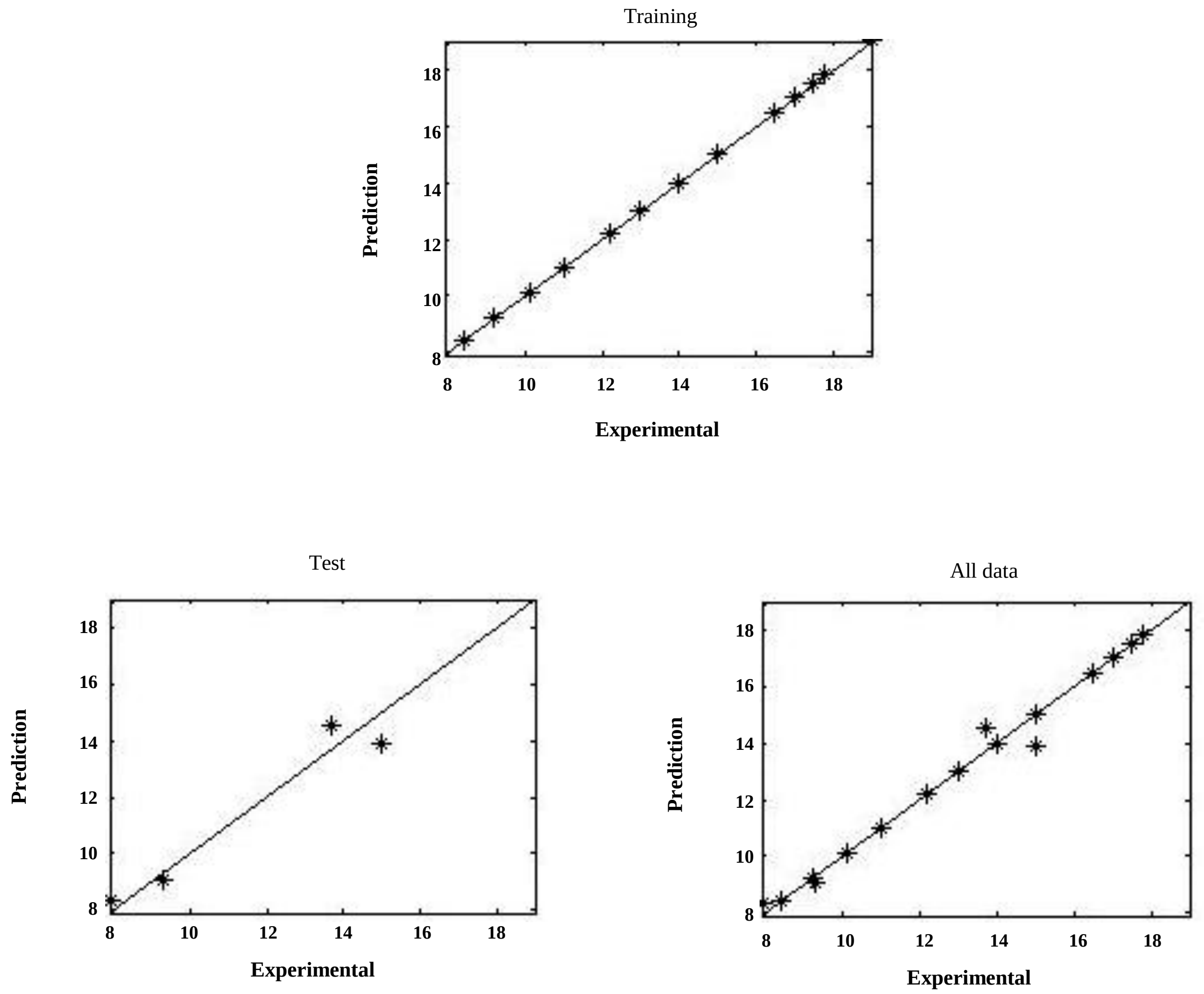

Fig. 6: Experimental values versus prediction.

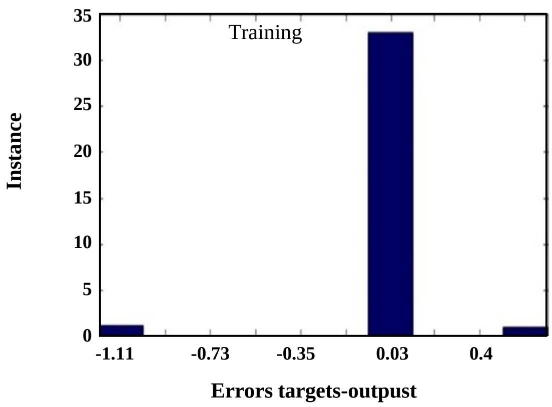

Fig. 7: Error disturbance histogram.

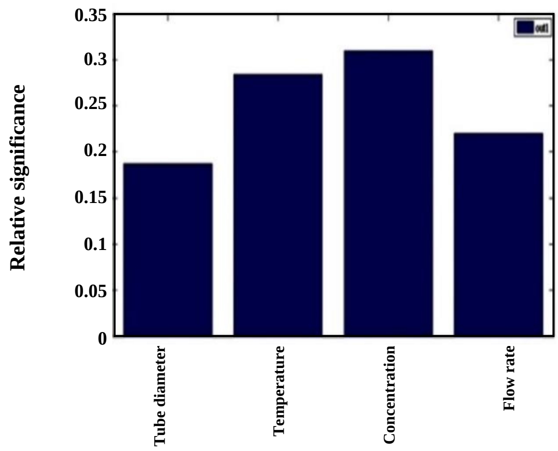

Fig. 8: Relative significance of input parameters on Drag.

Table 3: Lower bound and upper bond should have been mentioned.

Parameters	Lower bound	Upper bound
Tube Diameter(mm)	12.7	25.4
Temperature(^{0} C)	26	46
Concentration (ppm)	0.25	0.75
Flow rate (l/h)	700	1500

Table 4: Optimal values of parameters.

Parameters	Optimum value
Tube Diameter	12.7
Temperature	41.07
Concentration	0.628
Flow rate	1441.84
Drag reduction percentage	25.84%

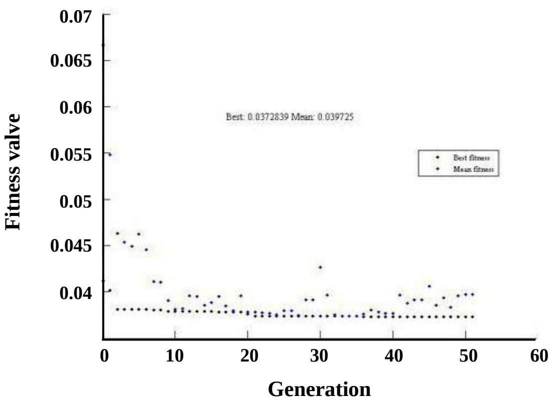

Fig. 9: The best condition has been achieved in 51 generations.

of nano concentration, flow rate, temperature, tube diameter were studied. Nanosio$_2$ was dissolved and homogenized in tap water by N,N,N,N Tetramethylethyldiamine surfactant using a stirrer and homogenizer. Tap water was 370 ppm total hardness and 7.6 pH. Nano SiO_2 was investigated at three concentrations of 0.25,0.5,0.75 ppm, and flow rate at 700,1000,1500l/h and temperatures of 26,36,46 ^{o} c and 12.7 and 25.4 mm galvanized iron pipes. The neural network system and the genetic algorithm were used to optimize and obtain the optimum. The neural network structure with an input layer consisting of four neurons which were related to processing variables, and an output layer with one neuron (drag reduction percent), were applied to this investigation. The high amount of R^2 for training, test, and all data, 0.9998,0.9890,0.9982 respectively, which were near to unity, show a negligible lack of fit, and validate the models' accuracy.

It was found that all four variables play a prominent role in the drag reduction percentage, and the optimum values for the form variables are 12.7 mm,41.07 0C,0.628 ppm,1441.84 l/h. Under these conditions, the experimental drag reduction amount reaches 25.7%, which is in accordance with the predictive amount of 25.84%.

Declarations: We confirm that the manuscript was read and approved by all named authors which there are no other persons who satisfied the criteria for authorship but are not listed.

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